

Bayesian Hierarchical Modelling Approaches to Indirect Treatment Comparisons between Single-arm Basket Trials: *An Application to NTRK-fusion Solid Tumours*

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Bayes 2024 Conference, Rockville, MD

Oct. 24, 2024

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• Opinions expressed are our own and do not necessarily reflect the views of Inka Health, AstraZeneca, Cytel, or the Centre for Reviews and Dissemination at the University of York

Background

- \triangleright Evaluating new drugs targeting rare cancer mutations/biomarkers can be extremely challenging due to difficulties recruiting enough patients
- Increased use of basket trial designs in recent years which recruit mutation/biomarker-positive patients with many different tumour types / histologies^{[\[1,](#page-14-0)2]}
- \triangleright These basket trials are typically phase I/II, lack a concurrent control arm, focus on response endpoints, and have limited sample sizes both overall and within each tumour histology
- \blacktriangleright The need for estimates of comparative effectiveness vs. standard-of-care to evaluate the cost-effectiveness of these new treatments for health technology assessment (HTA) has been highlighted–for both specific histologies and for tumour-agnostic consideration[\[3,](#page-14-2) [4,](#page-14-3) [5,](#page-14-4) [6\]](#page-14-5)

- \triangleright Our goal is to demonstrate an indirect treatment comparison (ITC) method for basket trials which:
	- \triangleright Compensates for potential confounding due to differences in histology composition between trials
	- \blacktriangleright Allows for partial pooling of information across histologies to improve precision/power where sample sizes are severely limited
	- \blacktriangleright Is implementable using aggregate data that is likely to be available from publications
- ► Our approach builds on some of our previous work, and established methods for applying BHMs in basket trial settings[\[7,](#page-14-6) [8,](#page-14-7) [9,](#page-14-8) [10,](#page-14-9) [11\]](#page-15-0)
- \triangleright We apply our approach to an ITC of two treatments–larotrectinib and entrectinib–studied in basket trial settings for NTRK-fusion positive solid tumours

 \triangleright Our model relies on several key assumptions:

- (i) Histologies are exchangeable (variability in prognosis across histologies can be modelled as random effects),
- (ii) The distribution of prognostic factors within each histology is similar between basket trials,
- (iii) There is overlap in included histologies between the two trials, and
- (iv) (Optionally) relative treatment effects are constant across histologies.
- \triangleright We consider an implementation that relaxes assumption (iv) by adding an additional random effect on the relative treatment effects

Model Setup

 \blacktriangleright We model the number of responders, r_{ik} , out of n_{ik} patients, for each basket trial $j \in \{0, 1\}$ and histology $k \in \{1, ..., K\}$ as follows:

> *r*_{*jk*} ∼ Binomial(n_{jk}, p_{jk}) $logit(p_{ik}) = \mu + d \cdot 1\{j = 1\} + \beta_k$ $\beta_k \sim \mathsf{N}(0, \sigma^2)$

- **If** where μ is an intercept term, *d* is the relative treatment effect, β_k is the random effect for the tumour histology k , and σ^2 is the histology random-effect variance.
- \triangleright We also consider a model variant which relaxes condition (iv) and instead assumes that relative treatment effects are also exchangeable across histologies, replacing *d* with

$$
\delta_k \sim \mathsf{N}(d,\tau^2)
$$

 \triangleright We opt to use weakly informative priors as follows:

$$
\mu \sim N\left(\text{logit}(0.1), \left[\frac{1}{1.96}(\text{logit}(0.9) - \text{logit}(0.1))\right]^2\right)
$$

$$
d \sim N\left(0, \left[\frac{1}{2 \cdot 1.96} \left(\ln(10) - \ln(0.1)\right)\right]^2\right)
$$

$$
\sigma, \tau \sim \text{Half-Cauchy}(0, 1)
$$

 \triangleright We estimate our posteriors via Markov chain Monte Carlo (MCMC) implemented in Stan[\[12\]](#page-15-1). We use 100,000 iterations with a burn-in of 10,000 for each of 4 chains. MCMC convergence was assessed through trace plots.

- \triangleright We use published aggregate data for entrectinib from the pooled phase-I ALKA-372-001 and STARTRK-1, and phase-II STARTRK-2 studies in adults with NTRK fusion-positive solid tumours[\[14\]](#page-15-2).
- \triangleright For larotrectinib we use published aggregate data for the pooled phase-I LOXO-TRK-14001 study in adults, phase-I/II SCOUT study in pediatric patients, and phase-II NAVIGATE study in pediatric and adult patients with NTRK-fusion-positive solid tumours[\[13\]](#page-15-3).
- \triangleright Using supplementary information from Hong et al. [\[13\]](#page-15-3), we attempt to remove all pediatric larotrectinib patients (a total of 51 patients of whom 47 were responders)

- \blacktriangleright Note that there are 102 larotrectinib patients split across 12 histologies
- \blacktriangleright There are 121 entrectinib patients split across 14 histologies
- \blacktriangleright Many histologies contain only a few patients and only 9 / 17 histologies are present for both treatments

Key Parameter Posteriors under Each Model vs. Priors (Dashed Line)

- \blacktriangleright We compare posteriors vs. priors for a pooled approach, our basic BHM, and our 2-random effect BHM ("2RE-BHM")
- \blacktriangleright Pooled treatment effect estimates (*d*)–the log odds ratio–are similar under all 3 models
- \blacktriangleright Evidence of modest heterogeneity in response across histologies but relatively minimal heterogeneity in relative treatment effect estimates

- \triangleright Point estimates of the odds ratio (OR) of response are similar across all 3 modelling approaches
- \triangleright 95% credible intervals (CrI) widen under the BHM and further widen under the 2RE-BHM, reflecting more uncertainty/restrained borrowing based on observed cross-histology heterogeneity
- \triangleright Posterior probability of superiority for larotrectinib is high under all 3 models, however 95% CrIs include an OR of 1

Histology-Specific Treatment Effect Estimates

• Posterior probability of superiority for larotrectinib is greater than 80% for all included tumour types, however, 95% CrIs still include OR of 1

 \blacktriangleright This method relies on several strong assumptions, key among them that:

- \blacktriangleright the random effects parameterization is considered to be an acceptable approximation for capturing cross-histology heterogeneity
- \blacktriangleright there are no major remaining imbalances in baseline characteristics beyond histology that are likely to confound the treatment effect estimates
- \triangleright Due to the severe data limitations encountered in basket trial settings, we argue that choice of ITC method should be viewed through the lens of determining an appropriate trade-off between precision and risk of bias

- \triangleright We demonstrate how a BHM ITC approach can be applied in practice to two drugs for NTRK-fusion positive solid tumours evaluated in single-arm basket trial settings
- \triangleright We argue that this BHM ITC approach is better-suited to basket trial settings than many established population-adjusted indirect comparison methods such as those outlined by the NICE Decision Support Unit[\[15\]](#page-15-4) (see also Mackay & Springford[\[16\]](#page-15-5) for a discussion of the advantages of Bayesian approaches for HEOR/HTA decision-making for rare diseases)
- \triangleright This approach can also be generalized to a comparison vs. an external control arm constructed using real-world data
- Manuscript preprint will be available very shortly–stay tuned!

References

- [1] Park JJ, Siden E, Zoratti MJ, Dron L, Harari O, Singer J, Lester RT, Thorlund K, Mills EJ. Systematic review of basket trials, umbrella trials, and platform trials: a landscape analysis of master protocols. Trials. 2019 Dec;20:1-0.
- [2] Tateo V, Marchese PV, Mollica V, Massari F, Kurzrock R, Adashek JJ. Agnostic approvals in oncology: getting the right drug to the right patient with the right genomics. Pharmaceuticals. 2023.
- [3] UK National Institute for Health and Care Excellence (NICE). Larotrectinib for treating NTRK fusion-positive solid tumours: technology appraisal guidance. 2020. https://www.nice.org.uk/guidance/ta630
- [4] UK National Institute for Health and Care Excellence. Entrectinib for treating NTRK fusion-positive solid tumours: technology appraisal guidance. 2020. https://www.nice.org.uk/guidance/ta644
- [5] Dayimu A, Demiris N, Lee K, Cromwell I, Heath A, Pechlivanoglou P. CADTH Health Technology Review: Bayesian Hierarchical Models of Basket Trials in the Context of Economic Evaluation. Canadian Journal of Health Technologies. 2024. https://www.cda-amc.ca/sites/default/files/hta-he/MH0020-Bayesian-Hierarchical-Models.pdf
- [6] Murphy P, Glynn D, Dias S, Hodgson R, Claxton L, Beresford L, Cooper K, Tappenden P, Ennis K, Grosso A, Wright K. Modelling approaches for histology-independent cancer drugs to inform NICE appraisals: a systematic review and decision-framework. Health technology assessment. 2022.
- [7] Mackay E, Springford A, Nagamuthu C, Dron L. A Bayesian Hierarchical Modelling Approach for Indirect Comparison of Response Outcomes in Histology-Independent Therapies [Abstract]. Value in Health. 2022 Dec. (Poster presented at ISPOR Europe 2022)
- [8] Mackay E, Springford A, Nagamuthu C, Dron L, Dias S. Bayesian Hierarchical Models for Indirect Treatment Comparisons of Histology-independent Therapies for Survival Outcomes [Abstract]. Value in Health. 2023 Jun.
- [9] Thall PF, Wathen JK, Bekele BN, Champlin RE, Baker LH, Benjamin RS. Hierarchical Bayesian approaches to phase II trials in diseases with multiple subtypes. Statistics in medicine. 2003 Mar 15;22(5):763-80.
- [10] Berry SM, Broglio KR, Groshen S, Berry DA. Bayesian hierarchical modeling of patient subpopulations: efficient designs of phase II oncology clinical trials. Clinical Trials. 2013 Oct;10(5):720-34.

- [11] Murphy P, Claxton L, Hodgson R, Glynn D, Beresford L, Walton M, Llewellyn A, Palmer S, Dias S. Exploring heterogeneity in histology-independent technologies and the implications for cost-effectiveness. Medical Decision Making. 2021 Feb:41(2):165-78.
- [12] Carpenter B, Gelman A, Hoffman MD, Lee D, Goodrich B, Betancourt M, Brubaker M, Guo J, Li P, Riddell A. Stan: A probabilistic programming language. Journal of statistical software. 2017 Jan 1;76(1).
- [13] Hong DS, DuBois SG, Kummar S, Farago AF, Albert CM, Rohrberg KS, van Tilburg CM, Nagasubramanian R, Berlin JD, Federman N, Mascarenhas L. Larotrectinib in patients with TRK fusion-positive solid tumours: a pooled analysis of three phase 1/2 clinical trials. The Lancet Oncology. 2020 Apr 1;21(4):531-40.
- [14] Demetri GD, De Braud F, Drilon A, Siena S, Patel MR, Cho BC, Liu SV, Ahn MJ, Chiu CH, Lin JJ, Goto K. Correction: Updated Integrated Analysis of the Efficacy and Safety of Entrectinib in Patients with NTRK Fusion–Positive Solid Tumors. Clinical Cancer Research. 2022 May 13;28(10):2196-.
- [15] Phillippo D, Ades T, Dias S, Palmer S, Abrams KR, Welton N. NICE DSU technical support document 18: methods for population-adjusted indirect comparisons in submissions to NICE. 2016. https://www.sheffield.ac.uk/media/34216/download?attachment
- [16] Mackay EK, Springford A. Evaluating treatments in rare indications warrants a Bayesian approach. Frontiers in Pharmacology. 2023.

Thank You!

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